Log-unbiased elastic image registration with spatial constraint for 3D CT lung images

Habib Y. Baluwala [1]
Kinda A. Saddi [2]
Julia A. Schnabel [1]

[1] Institute of Biomedical Engineering, Department of Engineering Science, University of Oxford, UK.
[2] Siemens Molecular Imaging, Oxford, UK.

Abstract

Registering diagnostic lung CT and whole body CT images is a difficult task due to their acquisition under different breathing stages. We have implemented a novel framework for 3D CT lung image registration which combines elastic registration with log-unbiased deformations and a spatially variable constraint to reduce image folding and retain the rigidity of the bones. A comparison of the proposed method, versus classic elastic registration on 3D phantom data, has shown that our algorithm has been successful in keeping the ribs and other bony structures rigid while reducing the amount of folding of the deformation field.

I. Introduction

Registering a diagnostic CT image to a whole body CT image used for PET attenuation correction is a very complex task for two reasons : (1) the volumes are acquired during different breathing stages; the whole body CT is obtained during passive breathing without any forced ventilatory movement, and the diagnostic lung CT is taken under deep inspiration for an enhanced view of the lung tissue (for better detection of tumours and viewing of the airways); (2) the diagnostic lung CT is acquired after the injection of a contrast agent whereas the whole body CT is acquired without contrast enhancement. Non-rigid image registration of the CT images is therefore necessary to establish spatial correspondence between the two volumes. A common problem with non-rigid registration techniques is that they treat the entire image as a flexible object and even rigid structures, such as the bones and the spine, are treated non-rigidly. The physical properties of the underlying structures are generally not taken into consideration while registering the images. One-to-one correspondence between the images is also desirable to avoid the appearance or disappearance of unwanted structures within the image. However, current registration techniques fail to meet both these conditions simultaneously leading to physically implausible solutions.

To date, there have been a few efforts in providing spatially varying or local regularization methods for image registration. One of the first inhomogeneous registration algorithms was proposed by Davatzikos [1], who used an inhomogeneous elastic model for registration of brain images. The method was designed to favour deformations in certain structures as specified by the user. However, the method was not able to recover very large deformations and was computationally very expensive. Other methods developed were a damped spring method [2], an inhomogeneous fluid registration [5], a finite element model [3] and a landmark based warp incorporating rigid structures [11]. However, none of these techniques have been applied for CT lung image registration. Staring *et al.* [8] proposed a method based on B-splines registration which uses subsequent filtering of the deformation field after a regular number of iterations to constrain the deformation of the bones. This method was used for registering CT lung images, but the results did not show a sufficient overlap of the rigid structures after registration.

Image registration is an ill-posed problem because multiple solutions exist, and the only way to reach to a particular solution is to add suitable constraints to the problem. The purpose of our work is to combine the advantages of different techniques in a new integrated framework that provides a physically plausible solution for registering whole body CT with diagnostic lung CT volumes. In this work, we will demonstrate the functionality and performance of this framework on a CT lung phantom dataset with different breathing stages.

II. Proposed Method:

Our proposed method extends the classic elastic registration model because of its suitability to model the physical behaviour of human tissue [6]. Elastic image registration is defined in terms of the Navier-Lamé linear partial differential equations where internal forces act as the regularizer and the deformation is driven by external forces [10]. The behaviour of the model in terms of the displacement vector field 'u' is represented by the following equation:

$$F = \mu \Delta \mathrm{u} + (\lambda + \mu) \nabla div(\mathrm{u}), \qquad (1)$$

where 'F' denotes the external forces. The derivation of the external force term is based on the similarity measure and optimization is achieved through the gradient descent method. The Lamé constants, 'λ' and 'μ', control the material properties of the elastic model. Since solving the equation in the above form is computationally expensive, we use the method presented by Fischer and Modersitzki [4] which utilizes the fast Fourier transform to obtain a fast direct solution for the large system of linear equations and avoids the necessity to invert the matrix associated with the system.

We also incorporate a statistical distribution of the Jacobian maps of the deformation field in the logarithmic space to produce unbiased transformations from the external force component, as suggested by the work of Yanovsky *et al.* [9]. This step constrains folding of the deformation field and yields a better distribution of the Jacobian maps within the image. The new external force component is given as:

$$F(R, M, u(x)) = \int_\Omega | R(x) - M(x) \circ s(x) \circ (Id + u(x)) |^2 \, dx + \gamma \int_\Omega J(u(x)) - 1 - \log | J(u(x)) | \, dx, \qquad (2)$$

where 'R' is the reference image, 'M' is the moving image, 'γ' is a weighting parameter, '$s(x)$' is the original transformation, 'Id' is the identity transform, '$\circ$' denotes the composition operator and $J(u)$ is the determinant of the Jacobian matrix of the deformation field which describes the change in the volume (compression or expansion) at the particular location.

To maintain the rigidity of the bones during the registration process and prevent any bending, we add the filtering technique of the deformation field as proposed in Staring *et al.*[5] into our framework. The spatially varying filter is applied to the deformation field after every iteration or after a specified number of iterations. The objective of the filter is to preserve the linearity of the deformations of the rigid tissue. This is achieved by calculating a weighted mean over a small neighbourhood (Ω_x), as shown below:

$$m(x) \triangleq \sum_{x\epsilon\Omega_x} c(x)u(x) / \sum_{x\epsilon\Omega_x} c(x), \tag{3}$$

where c(x) is the stiffness coefficient map with values between 0 (for nonrigid structures) and 1 (for rigid structures such as bone) . The current experiment uses a 5 x 5 x 5 neighbourhood for the filter while the stiffness map for the bones is obtained using thresholding of the intensity values. The filtered deformation field is then defined by assigning a value close to the mean deformation if the tissue is rigid, and a value close to the original deformation otherwise. The estimation for the resultant deformation field is shown in Eq (4):

$$u_{New}(x) \triangleq (1 - c(x))u(x) + c(x)m(x) \tag{4}$$

III. Experiments and Results

The proposed algorithm was tested on a phantom dataset generated using the 4D NURBS-based Cardiac-Torso (NCAT phantom) toolkit developed by Segars [7]. The 4D NCAT phantom is a realistic and flexible simulation tool for generating CT volumes and modelling cardiac and respiratory motion. Five volumes have been generated representing different stages of a breathing cycle having a resolution of 192 x 192 x 192 voxels. The voxel size in each direction is 0.48 mm. Gaussian noise was added to the images to test the robustness of the algorithms.

The proposed method has been compared with the standard elastic registration technique that has the same underlying transformation model as our proposed method. The accuracy of the proposed method has been validated by measuring the volume overlap of the organs (such as the lungs, liver, ribs and spine) in the reference and the moving image after registration. The overlap ratio (also named Dice Coefficient) used is defined as:

$$\text{Overlap ratio} \triangleq 2|V_1 \cap V_2| / (|V_1| + |V_2|), \tag{5}$$

where V_1 and V_2 are the volumes representing a particular organ in the reference and the moving image. We also compare the percentage of folding that occurs in both methods, estimated from the Jacobian determinant values of the deformation field. The different stages of the breathing cycles have been registered with one another. A coarse-to-fine multi-resolution strategy was used to recover large deformations. Three levels of resolution were used for both registration algorithms, and 250 iterations were performed for each level. The stiffness coefficient map c(x) was calculated by binary thresholding of the CT volume. The Dice's coefficients were calculated for each organ and each registration, and were then averaged. The average volume overlap values, displayed in Table 1, confirm that the proposed method has a better overlap for the major organs as compared to the standard elastic registration, especially in ribs and spine and to a lesser degree in the lungs. This can be expected because the lung is compressible/expandable organ where the deformations will be largest. Visual inspection of Figure 1 confirms that the proposed method has superior performance. Figure 1 also shows that the proposed method preserves the rigidity of the bone by restricting the deformation. The average percentage of folding of the deformation field that occurs in the general elastic registration method is 0.1 % while this percentage is reduced to only 0.007% after registering the volumes using our proposed method.

Method	Ribs	Spine	Lung	Liver	Average
Before Registration	0.7797	0.9355	0.8339	0.7342	0.8208
Elastic registration	0.9021	0.9214	0.9820	0.9211	0.9316
Proposed method	0.9638	0.9538	0.9756	0.9423	0.9589

Table 1. Average overlap (Dice coefficient) of the organs

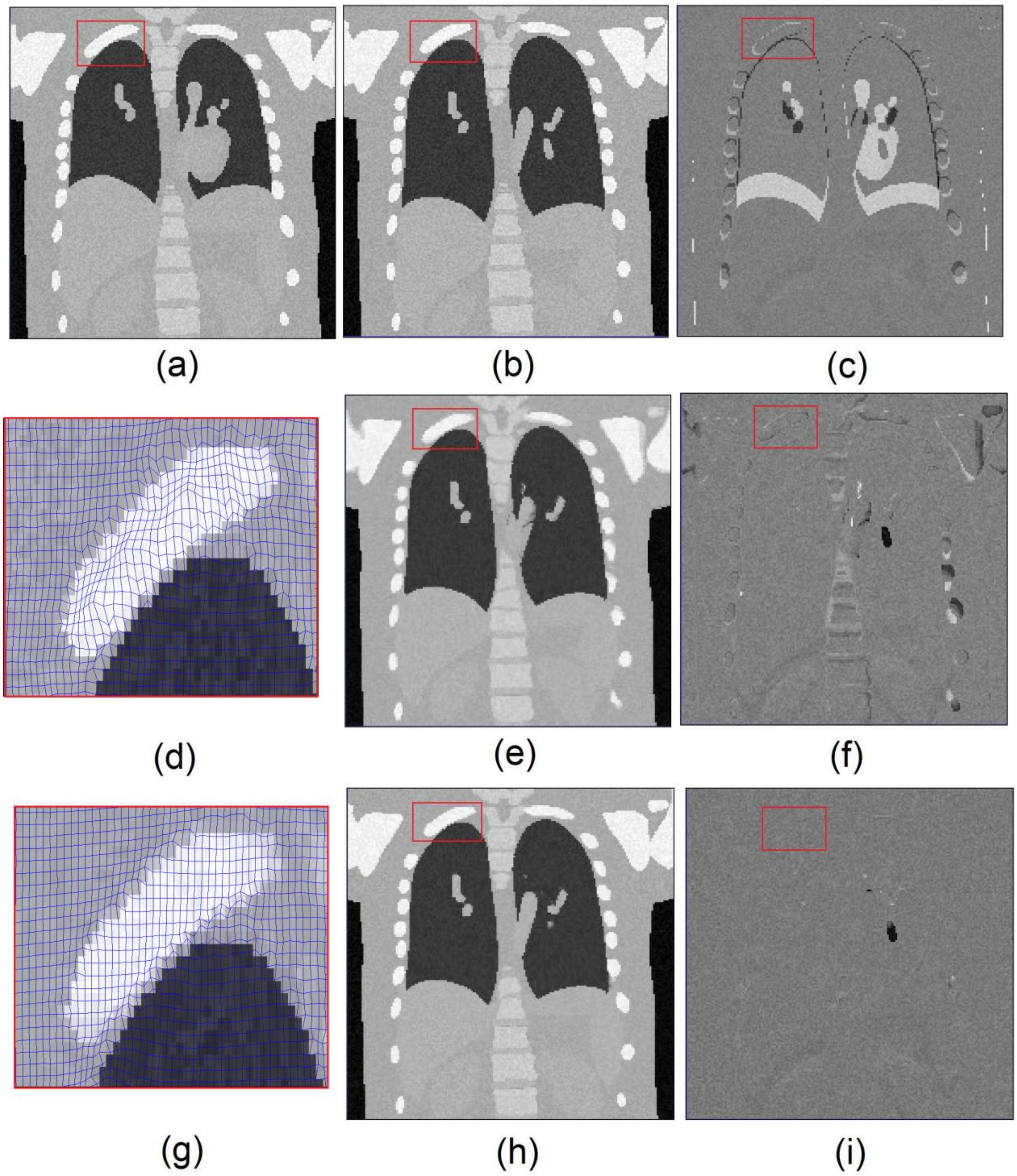

Figure 1: Example slices of 3D registration results (a) Moving Image, (b) Reference Image, (c) Difference Image before registration, (e) Transformed image after elastic registration, (f) Difference Image after elastic registration, (h) Transformed image after registration with the proposed method, (i) Difference image after registration with the proposed method. Zoomed image of the bone (labelled by red box in the other images) with the deformation field (d) Using elastic registration, (g) Using proposed method.

IV. Discussion and Conclusion

In traditional non-rigid registration techniques, the entire image is treated with the same physical properties, which can result in physically implausible deformation of rigid structures. In this paper, we have presented a new framework that successfully combines elastic registration with log unbiased deformations and spatial constraints for bone rigidity. Our proposed method was quantitatively evaluated on the NCAT phantom and its comparison with the standard elastic registration technique shows that our method has a superior performance. The organ overlap ratios and the Jacobian values indicate that our method has performed well in preserving the rigidity of the bones and in preserving image topology. Hence, our method is able to model locally rigid motion and find a physically plausible solution for the given registration problem. Our future work focuses on extending this framework to accommodate for registration of contrast enhanced diagnostic lung CT volumes to whole body CT volumes.

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VI. References

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